2. Knight DR, Elliott B, Chang BJ, Perkins TT, Riley TV. Diversity and evolution in the genome of *Clostridium difficile*. Clin Microbiol Rev. 2015;28:721–41. https://doi.org/10.1128/CMR.00127-14
3. Monot M, Eckert C, Lemire A, Hamiot A, Dubois T, Tessier C, et al. *Clostridium difficile*: new insights into the evolution of the pathogenicity locus. Sci Rep. 2015;5:15023. https://doi.org/10.1038/srep15023
4. Ramírez-Vargas G, López-Ureña D, Badilla A, Orozco-Aguilar J, Murillo T, Rojas P, et al. Novel Clade C-I *Clostridium difficile* strains escape diagnostic tests, differ in pathogenicity potential and carry toxins on extrachromosomal elements. Sci Rep. 2018;8:13951. https://doi.org/10.1038/s41598-018-32390-6

Address for correspondence: César Rodríguez, Universidad de Costa Rica, Facultad de Microbiología, Ciudad Universitaria Rodrigo Facio, San Pedro de Montes de Oca, 11501-2060, San José, Costa Rica; email: cesar.rodriguezsanchez@ucr.ac.cr

Information-Accessing Behavior during Zika Virus Outbreak, United States, 2016

Rachael Piltch-Loeb, David Abramson

Author affiliation: New York University, New York, New York, USA

DOI: https://doi.org/10.3201/eid2609.191519

We used latent class analysis to examine Zika virus–related information-accessing behavior of US residents during the 2016 international outbreak. We characterized 3 classes of information-accessing behavior patterns: universalists, media seekers, and passive recipients. Understanding these patterns is crucial to planning risk communication during an emerging health threat.

During the past 15 years, new media platforms have emerged as routine channels of health communication. Little is known about how persons navigate this dynamic and complex information landscape, especially during an emerging health threat with little scientific certainty and few or no medical countermeasures (*1*,*2*). The 2016 Zika virus outbreak provides for an examination of how people interact with this dynamic information landscape. As scientific understanding of the virus evolved, so did Zika risk communication strategies. Previous reports have identified public sources of Zika information but have not considered the public's information-accessing behavior (*3*,*4*). We used latent class analysis (LCA) to characterize and differentiate types of information-accessing behavior and identify how these behavioral patterns shifted during the 2016 Zika virus outbreak.

LCA identifies clusters within the population on the basis of participants' responses to observed variables (*5*,*6*). We collected and pooled data from 3 representative samples of US households drawn from fully replicated, single-stage, random-digit dialing samples of households supplemented by lists of randomly generated cell phone numbers. The survey had a 4%–6% response rate. We conducted the surveys in April–May (1,233 participants), July–August (1,231 participants), and October–November (1,234 participants) of 2016.

The survey analyzed access to 6 categories of information sources: news (online or print); television or radio; social media, such as Facebook, YouTube, Reddit, or other apps; personal physician; government agencies; and friends, family, or co-workers. We used these data to form 6 binary variables indicating access to each category of information source. We then used these variables to determine 3 classes of information-accessing behavior.

In accordance with the best practices suggested by Nylund et al. (*7*), we used 6 criteria to determine the optimal number of classes (Appendix, https://wwwnc.cdc.gov/EID/article/26/9/19-1519-App1.pdf). New York University's Institutional Review Board approved this research.

Our LCA results suggested that information-accessing behaviors could be grouped into 3 distinct classes: universalists, media seekers, and passive recipients. We sorted each participant into a class on the basis of the number of sources he or she had accessed (Figure). Class 1 comprised universalists, that is, participants who actively accessed information from all sources included in the survey. Class 2 comprised media seekers, that is, participants who primarily accessed information from mass media. Class 3 comprised passive recipients of information; these participants accessed the fewest number of sources and had the highest probability of seeking information from broadcast media. Class membership was not necessarily static; an individual participant might exhibit different information-accessing behaviors at different time points within the Zika outbreak.

The acquisition patterns of Zika information shifted across time. At the first time point (April–May 2016), universalists constituted 23.0% of the US population, media seekers 20.7%, and passive recipients 54.3%. At the second time point (July–August 2016),

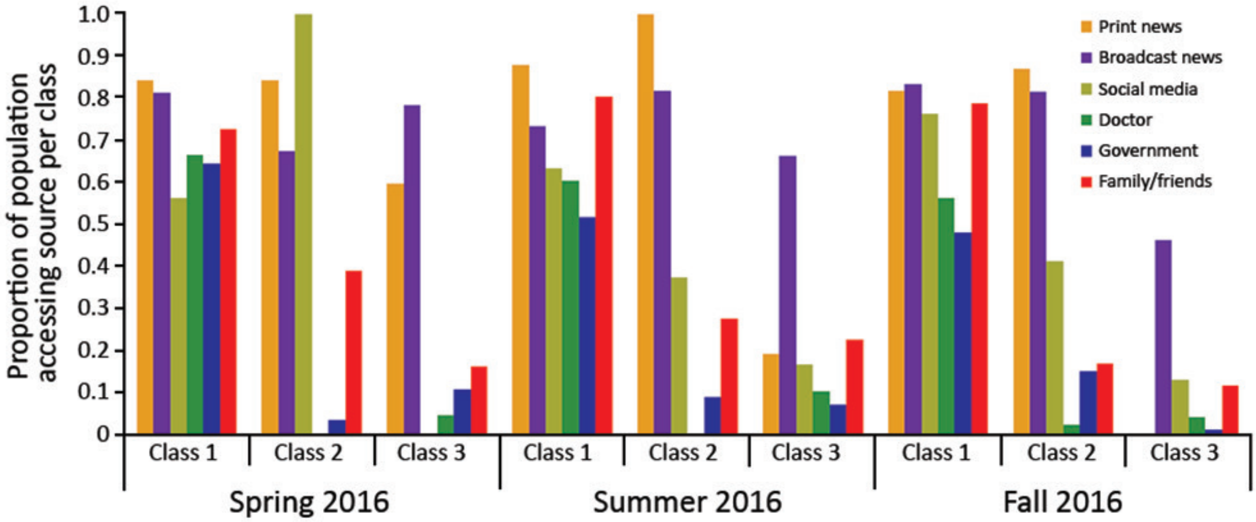

Figure. Latent classes of information access for Zika virus, United States, 2016. Proportion of the population that used a given category of information source in each class, across 3 time points of data collection.

universalists constituted 13.8% of the population, media seekers 51.5%; and passive recipients 34.8%. At the third time point (October–November 2016), universalists constituted 16.0% of the population, media seekers 52.0%, and passive recipients 32.0%.

As understanding of Zika virus evolved and media coverage shifted, the proportion of the population in each of the identified classes also shifted. Our finding that the proportion of the population in the universalist group was largest at the first time point suggests that in the earlier phases of the Zika outbreak, acquisition of information increased among the most highly attuned portions of the population. We hypothesize that as the mosquito season began, behavior patterns shifted from passive information acquisition to active information acquisition in the shift to media seeking (*8*). This hypothesis explains the shift from the large proportion of passive recipients at the first time point to the larger proportions of media seekers at the second and third time points.

These population shifts suggest large portions of the population were initially passive, perhaps uninterested, recipients of information about Zika. During the course of the surveys, a proportion of passive recipients and universalists may have become media seekers. In addition, we found that early adopters of emerging information could be retransmitters within their networks. Only universalists consistently accessed information from their own social network (including personal contacts and social media), the medical community, and government sources. Further exploration is needed to determine whether these findings are influenced by the actual lack of risk for Zika in the United States or whether they are reflective of larger behavioral patterns.

Our analysis is limited by the number of information source categories included in the survey and the lack of source specificity. However, our study took a unique approach in characterizing patterns of information-accessing behavior. These findings can be used to inform risk communication strategies designed for population segments with different information-accessing behavior patterns.

This study was funded by National Science Foundation under Rapid Response Research grant no. 1638545.

About the Authors

Dr. Piltch-Loeb is a Preparedness Fellow at the Harvard T.H. Chan School of Public Health. She completed this work as part of her doctorate in the department of Social and Behavioral Sciences at New York University Global Public Health. Her research interests include public health emergencies and risk communication.

Dr. Abramson is a clinical associate professor in the department of Social and Behavioral Sciences at New York University Global Public Health. His research interests include public health disaster science.

References

1. Anker AE, Reinhart AM, Feeley TH. Health information seeking: a review of measures and methods. Patient Educ Couns. 2011;82:346–54. https://doi.org/10.1016/j.pec.2010.12.008
2. Jacobs W, Amuta AO, Jeon KC. Health information seeking in the digital age: an analysis of health information seeking

behavior among US adults. Cogent Soc Sci. 2017;3:1302785. https://doi.org/10.1080/23311886.2017.1302785
3. Piltch-Loeb R, Merdjanoff AA, Abramson DM. How the US population engaged with and prioritized sources of information about the emerging Zika virus in 2016. Health Secur. 2018;16:165–77. https://doi.org/10.1089/hs.2017.0107
4. Sell TK, Watson C, Meyer D, Kronk M, Ravi S, Pechta LE, et al. Frequency of risk-related news media messages in 2016 coverage of Zika virus. Risk Anal. 2018;38:2514–24. https://doi.org/10.1111/risa.12961
5. Wolfe JH. Pattern clustering by multivariate mixture analysis. Multivariate Behav Res. 1970;5:329–50. https://doi.org/10.1207/s15327906mbr0503_6
6. Goodman LA. The analysis of systems of qualitative variables when some of the variables are unobservable. Part IA modified latent structure approach. The American Journal of Sociology. 1974;79:1179–259. https://doi.org/10.1086/225676
7. Nylund KL, Asparouhov T, Muthén BO. Deciding on the number of classes in latent class analysis and growth mixture modeling: a Monte Carlo simulation study. Struct Equ Modeling. 2007;14:535–69. https://doi.org/10.1080/10705510701575396
8. Agarwal NK. Information source and its relationship with the context of information seeking behavior. In: iConference 2011: proceedings of the 2011 iConference; 2011 Feb 8–11; Seattle, Washington, USA. New York: Association for Computing Machinery; 2011. p. 48–55.

Address for correspondence: Rachael Piltch-Loeb, New York University, Global Public Health, 715 Broadway Rm 1229, New York, NY 10003, USA; email: rpl5@nyu.edu

Severe Fever with Thrombocytopenia Syndrome Virus in Ticks and SFTS Incidence in Humans, South Korea

Jeong Rae Yoo,[1] Sang Taek Heo,[1] Sung Wook Song, Seung Geon Bae, Seul Lee, Sungho Choi, Chaehyun Lee, Sugyeong Jeong, Myeongseop Kim, Woojin Sa, Yeongrim Lee, Haseon Choi, Sun-Ho Kee, Keun Hwa Lee

DOI: https://doi.org/10.3201/eid2609.200065

[1]These authors contributed equally to this article.

Author affiliations: Jeju National University, Jeju, South Korea (J.R. Yoo, S.T. Heo, S.W. Song, S.G. Bae, S. Lee, S. Choi, C. Lee, S. Jeong, M. Kim, W. Sa, Y. Lee, H. Choi); Korea University, Seoul, South Korea (S.-H. Kee); Hanyang University College of Medicine, Seoul (K.H. Lee).

During 2016–2018, we collected 3,193 ticks from rural areas in South Korea to investigate the prevalence of severe fever with thrombocytopenia syndrome virus (SFTSV). We detected SFTSV in ticks at an infection rate (IR) of 11.1%. We noted increases in the human IR associated with the monthly SFTSV IR in ticks.

Severe fever with thrombocytopenia syndrome (SFTS) is a tickborne zoonosis caused by the SFTS virus (SFTSV) (*1*); >1,000 SFTS cases have been reported in South Korea (*2*). The SFTS prevalence rate was 2.26/100,000 inhabitants on the mainland and 13.66/100,000 inhabitants on Jeju Island, South Korea (*2*). SFTSV has been detected in several species of ticks, including *Haemaphysalis longicornis*, *Amblyomma testudinarium*, and *Ixodes nipponensis* (*3*). A previous study reported that the minimum infection rate of SFTSV in infected ticks was lower (0.37%) on Jeju Island than in other collection areas (1.97%) (*4*). However, 7%–14% SFTSV seropositivity was identified in domestic and wild animals (*4*–*5*), and 2%–5% SFTSV seropositivity was identified in a healthy population in South Korea (*6*). Therefore, our aim was to investigate the SFTSV infection rate (IR) in ticks in the region with the highest endemicity, Jeju Island, and to analyze the relationship between the geographic distribution of ticks and SFTSV and human cases of SFTS.

During June 2016–January 2019, well-equipped trained researchers collected ticks from the natural environment of Jeju Island. The tick sampling sites included 5 rural areas: Aewol-eup (AW); Seon Hul-ri (SH); Jeo Ji-ri (JJ); and Ha Do-ri (HD) and Bo Mok-ri (BM) (Figure). These 5 areas were chosen to compare SFTSV IR in ticks in areas with the highest rates of human SFTS cases, SH, HD, and AW, and SFTSV IR in ticks in areas with lower human SFTS rates, JJ and BM. Ticks were manually collected 2 times per month, during the first and third weeks, by dragging a white cloth in woodlands for 2 hours in each area. We morphologically identified tick species and developmental stages by using an Olympus SD-ILK-200–2 stereomicroscope (Olympus Corporation, https://www.olympus-lifescience.com) (*7*) and extracted viral RNA by using a QIAamp Viral RNA Mini kit (QIAGEN Inc., https://www.qiagen.com) according to the manufacturer's instructions (Appendix, https://wwwnc.cdc.gov/EID/article/26/9/20-0065-App1.pdf).

Article DOI: https://doi.org/10.3201/eid2607.191519

Information-Accessing Behavior During Zika Virus Outbreak, United States, 2016

Appendix

Methods

Data Source

Three cross-sectional samples of the United States population were collected at three distinct time points—Spring (April/May), Summer (July/August), and Fall (October/November) of 2016—which included measures related to source of Zika information. Data was collected from a representative sample of U.S. households collected using a fully-replicated, single-stage, random-digit-dialing (RDD) sample households supplemented by a list of randomly generated cell phone numbers. The first structured telephone survey was of 1,233 U.S. residents, subsequent surveys sampled 1,231 residents and 1,234 residents respectively. Data will be analyzed using complex survey weights so results are representative of the population. Further information on weighting procedures have been described in detail in a previous manuscript (*1*).

Analytic Plan

Statistical methods such as LCA are especially useful to understand if there are underlying subtypes of individuals in the population for the phenomena at hand. LCA will be used to identify if there are "types" of information users within the population. LCA is a statistical tool to study a heterogeneous population consisting of several unidentified groups who behave differently regarding the problem at hand. LCA functions in terms of probability, specifically the probability that an individual belongs to a particular scoring pattern among the observed variables (*2*). While there are multiple interpretations of latent classes, the one being explored here is to classify respondents into being a member of a latent, unobserved class on the basis of their responses to one or more observed variables (*3*). LCA can reduce analytic complexity by identifying patterns of activity (*4*). Cluster analysis and LCA techniques have been used within the fields of psychology, organizational behavior, and political science, and applied to examining health behaviors (*2,5–11*).

Model Selection

There is some debate in best practices for LCA model selection, especially when applying weighted population estimates when likelihood ratio tests may not be appropriately run since maximum likelihood estimates are not possible (*12*). In accordance with the best practices set out by Nylund, Asparaouhov, & Muthen (2007), several criteria were used to determine the optimal number of classes (*13*). The criteria applied here were:

1. Akaike and Bayesian information criteria (AIC and BIC) (*14*);
2. Lo-Mendell-Rubin adjusted likelihood ratio test;
3. Entropy;
4. the relative size of classes in each model;
5. substantive interpretability;
6. and replication of the LCA solution in all three samples.

Results

LCA results suggested a replicable three-class solution of information users in the population, with classes distinguished by the number of sources accessed. Appendix Tables 1–3 demonstrate the selection criteria used to compare 2–6 classes and reflect the three classes solution had the best goodness of fit at each time point. Results as to the proportion of the population in each class and accessing each source by time point are below in Appendix Tables 4–6.

Sample 1: Spring 2016

The proportion of the population in each of the three-classes is shown in Appendix Table 1. The average latent class probability, an indicator of membership within a latent class, measures how certain an individual is to be in one class compared to another, was high- 0.944, 0.893, and 0.906 respectively. Within Class 1, the probability of getting information from print news was 0.845, broadcast news was 0.814, social media was 0.564, doctor was 0.667, government was 0.645, and family/friends was 0.729. Within Class 2, the probability of getting information from print news was 0.844, broadcast news was 0.675, social media was 1.00, doctor was 0.00, government was 0.035, and family/friends was 0.390. Within Class 3, the probability of getting information from print news was 0.597, broadcast news was 0.786, social media was 0.004, doctor was 0.047, government was 0.108, and family/friends was 0.164.

Sample 2: Summer 2016

The proportion of the population in each of the three-classes is shown in Appendix Table 2. From time 1 to time 2, the proportion of the population in each class shifted. Class 1, people who sought information from many sources, was 13.8% of the population, Class 2, those who primarily sought information from mass media and social media were 51.5% of the population, and Class 3, the least active information seekers, was 34.7% of the population. The average latent class probability, an indicator of membership within a latent class, measures how certain an individual is to be in one class compared to another, was still high- 0.890, 0.792, and 0.947 respectively. For Class 1, the probability of getting information from print news was 0.881, broadcast news was 0.735, social media was 0.635, doctor was 0.605, government was 0.518, and family/friends was 0.806. Within Class 2, the probability of getting information from print news was 1.00, broadcast news was 0.818, social media was 0.376, doctor was 0.00, government was 0.090, and family/friends was 0.277. Within Class 3, the probability of getting information from print news was 0.193, broadcast news was 0.665, social media was 0.169, doctor was 0.105, government was 0.073, and family/friends was 0.227.

Sample 3: Fall 2016

The proportion of the population in each of the three-classes is shown in Appendix Table 3. The proportion of the population in each class was similar to Sample 2. The average latent class probability, an indicator of membership within a latent class, measures how certain an individual is to be in one class compared to another, was also high- 0.852, 0.860, 0.872- respectively. For Class 1, the probability of getting information from print news was 0.818, broadcast news was 0.834, social media was 0.764, doctor was 0.564, government was 0.482, and family/friends was 0.789. Within Class 2, the probability of getting information from print news was 0.871, broadcast news was 0.816, social media was 0.414, doctor was 0.024, government was 0.151, and family/friends was 0.171. Within Class 3, the probability of getting information from print news was 0.000, broadcast news was 0.463, social media was 0.131, doctor was 0.044, government was 0.014, and family/friends was 0.118.

References

1. Piltch-Loeb R, Abramson DM, Merdjanoff AA. Risk salience of a novel virus: US population risk perception, knowledge, and receptivity to public health interventions regarding the Zika virus prior to local transmission. PLoS One. 2017;12:e0188666. PubMed https://doi.org/10.1371/journal.pone.0188666

2. Hagenaars JA, McCutcheon AL. Applied latent class analysis. Cambridge: Cambridge University Press; 2002.

3. Goodman LA. The analysis of systems of qualitative variables when some of the variables are unobservable. Part IA modified latent structure approach. American Journal of Sociology. 1974;79:1179–259. https://doi.org/10.1086/225676

4. Lanza ST, Rhoades BL. Latent class analysis: an alternative perspective on subgroup analysis in prevention and treatment. Prev Sci. 2013;14:157–68. PubMed https://doi.org/10.1007/s11121-011-0201-1

5. Bucholz KK, Heath AC, Reich T, Hesselbrock VM, Krarner JR, Nurnberger JI Jr, et al. Can we subtype alcoholism? A latent class analysis of data from relatives of alcoholics in a multicenter family study of alcoholism. Alcohol Clin Exp Res. 1996;20:1462–71. PubMed https://doi.org/10.1111/j.1530-0277.1996.tb01150.x

6. Hudziak JJ, Heath AC, Madden PF, Reich W, Bucholz KK, Slutske W, et al. Latent class and factor analysis of DSM-IV ADHD: a twin study of female adolescents. J Am Acad Child Adolesc Psychiatry. 1998;37:848–57. PubMed https://doi.org/10.1097/00004583-199808000-00015

7. Clatworthy J, Buick D, Hankins M, Weinman J, Horne R. The use and reporting of cluster analysis in health psychology: a review. Br J Health Psychol. 2005;10:329–58. PubMed https://doi.org/10.1348/135910705X25697

8. Kendler KS, Karkowski LM, Walsh D. The structure of psychosis: latent class analysis of probands from the Roscommon Family Study. Arch Gen Psychiatry. 1998;55:492–9. PubMed https://doi.org/10.1001/archpsyc.55.6.492

9. Kiel GC, Layton RA. Dimensions of consumer information seeking behavior. Journal of Marketing Research. 1981;18:233–9. https://doi.org/10.1177/002224378101800210

10. Laska MN, Pasch KE, Lust K, Story M, Ehlinger E. Latent class analysis of lifestyle characteristics and health risk behaviors among college youth. Prev Sci. 2009;10:376–86. PubMed https://doi.org/10.1007/s11121-009-0140-2

11. Punj G, Stewart DW. Cluster analysis in marketing research: review and suggestions for application. Journal of Marketing Research. 1983;20:134–48. https://doi.org/10.1177/002224378302000204

12. Korn EL, Graubard BI. Simultaneous testing of regression coefficients with complex survey data: use of Bonferroni t statistics. Am Stat. 1990;44:270–6. https://doi.org/10.2307/2684345

13. Nylund KL, Asparouhov T, Muthén BO. Deciding on the number of classes in latent class analysis and growth mixture modeling: a Monte Carlo simulation study. Struct Equ Modeling. 2007;14:535–69. https://doi.org/10.1080/10705510701575396

14. Muthén BO. Latent variable mixture modeling. In: Muthén BO, Marcoulides GA, editors. New developments and techniques in structural equation modeling. New York: Psychology Press; 2001. p. 21-54.

Appendix Table 1. Model fit statistics of latent class analysis models on Zika information accessing behaviors. United States, April–May 2016

No. classes	H0 value	H0 scaling correction factor for MLR	AIC	BIC	SBIC	Entropy	Pearson's χ^2 p value	LLR χ^2 p value	Average LC probability for most likely LC	Lo Mendell Rubin p value	Vuong Lo Mendell Rubin p value
2 class model	–4,070.212	2.0027	8,166.425	8,232.948	8,191.655	0.611	<0.01	<0.01	0.844, 0.911	<0.01	<0.01
3 class model	-4,021.901	1.6961	8,083.802	8,186.146	8,122.618	0.804	<0.01	<0.01	0.944, 0.893, 0.906	<0.01	<0.01
4 class model	–3,986.520	1.8278	8,027.040	8,165.204	8,079.441	0.829	0.04	<0.01	0.865, 0.849, 0.906, 0.946	0.36	0.36
5 class model	–3,964.701	1.5854	7,997.402	8,171.387	8,063.388	0.700	0.99	0.03	0.887, 0.816, 0.891, 0.560, 0.889	0.19	0.19

LC, latent class; AIC, Aikake Information criteria; BIC, Bayesian information criteria; MLR, multi-linear regression; LLR, log linear ratio

Appendix Table 2. Model fit statistics of latent class analysis models on Zika information accessing behaviors. United States, July–August 2016

No. classes	H0 Value	H0 Scaling Correction Factor for MLR	AIC	BIC	SBIC	Entropy	Pearson's χ^2 p value	LLR χ^2 p value	Average LC probability for most likely LC	Lo Mendell Rubin p value	Vuong Lo Mendell Rubin p value
2 class model	–3,968.288	2.0518	7,962.576	8,029.068	7,987.775	0.712	<0.01	<0.01	0.758, 0.953	0.02	0.02
3 class model	–3,932.758	1.7150	7,905.516	8,007.812	7,944.283	0.653	<0.01	<0.01	0.890, 0.792, 0.947	0.06	0.06
4 class model	–3,907.997	1.5895	7,869.994	8,008.093	7,922.330	0.738	<0.01	<0.01	0.920, 0.822, 0.864, 0.850	0.13	0.13
5 class model	–3,893.733	1.8898	7,855.467	8,029.369	7,921.371	0.695	<0.01	0.02	0.794, 0.779, 0.712, 0.922, 0.807	0.74	0.74

LC, latent class; AIC, Aikake Information criteria; BIC, Bayesian information criteria; MLR, multi-linear regression; LLR, log linear ratio

Appendix Table 3. Model fit statistics of latent class analysis models on Zika information accessing behaviors. United States, October–November 2016

No. classes	H0 Value	H0 Scaling Correction Factor for MLR	AIC	BIC	SBIC	Entropy	Pearson's χ^2 p value	LLR χ^2 p value	Average LC probability for most likely LC	Lo Mendell Rubin p value	Vuong Lo Mendell Rubin p value
2 class model	–3,934.742	1.7497	7,895.485	7,962.008	7,920.715	0.571	<0.01	<0.01	0.917, 0.797	<0.01	<0.01
3 class model	–3,864.304	1.5507	7,768.608	7,870.952	7,807.423	0.699	0.40	0.03	0.852, 0.860, 0.872	<0.01	<0.01
4 class model	–3,850.260	1.4955	7,754.520	7,892.685	7,806.921	0.645	0.98	0.21	0.818, 0.973, 0.682, 0.846	0.26	0.25
5 class model	–3,839.352	1.3971	7,746.703	7,920.688	7,812.690	0.608	1.00	0.58	0.780, 0.686, 0.812, 0.721, 0.929	0.21	0.22

LC, latent class; AIC, Aikake Information criteria; BIC, Bayesian information criteria; MLR, multi-linear regression; LLR, log linear ratio

Appendix Table 4**.** Latent class analysis proportions and Zika information sources. United States, April–May 2016

Class category	Class 1	Class 2	Class 3
Proportion of population in class*	0.23030	0.20710	0.54259
Information source, % use (SE)			
Print news	0.845 (0.041)	0.844 (0.072)	0.597 (0.026)
Broadcast news	0.814 (0.040)	0.675 (0.043)	0.786 (0.023)
Social media	0.564 (0.057)	1.000 (0.000)	0.004 (0.095)
Doctor	0.667 (0.071)	0.000 (0.000)	0.047 (0.020)
Government	0.645 (0.050)	0.035 (0.040)	0.108 (0.025)
Family and friends	0.729 (0.060)	0.390 (0.077)	0.164 (0.023)

*<2% of the population could not be adequately sorted into a class

Appendix Table 5. Latent class analysis proportions and Zika information sources. United States, July–August 2016

Class category	Class 1	Class 2	Class 3
Proportion of population in class	0.13775	0.51486	0.34739
Information source, % use (SE)			
Print news	0.881 (0.084)	1.00 (0.000)	0.193 (0.144)
Broadcast news	0.735 (0.060)	0.818 (0.030)	0.665 (0.032)
Social media	0.635 (0.0.88)	0.376 (0.050)	0.169 (0.031)
Doctor	0.605 (0.110)	0.000 (0.000)	0.105 (0.037)
Government	0.518 (0.083)	0.090 (0.024)	0.073 (0.032)
Family and friends	0.806 (0.099)	0.277 (0.047)	0.227 (0.033)

Appendix Table 6. Latent class analysis proportions and Zika information sources. United States, October–November 2016

Class category	Class 1	Class 2	Class 3
Proportion of population in class	0.16000	0.52000	0.32000
Information source, % use (SE)			
Print news	0.818 (0.046)	0.871 (0.086)	0.000 (0.000)
Broadcast news	0.834 (0.039)	0.816 (0.023)	0.463 (0.061)
Social media	0.764 (0.043)	0.414 (0.041)	0.131 (0.042)
Doctor	0.564 (0.116)	0.024 (0.017)	0.044 (0.014)
Government	0.482 (0.074)	0.151 (0.022)	0.014 (0.021)
Family and friends	0.789 (0.065)	0.171 (0.054)	0.118 (0.025)